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Evaluating the Effectiveness of Classical Denoising Filters for Microcalcification Segmentation in Mammogram

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***Abstract* —** One of the vital signs of early breast cancer is calcification in breast masses. Although calcification has been a principal indicator of malignant tumor in breast imaging treatment, accurate detection and interpretation of calcification using mammograms remain challenging, which is mainly due to their tiny sizes, heterogeneous structures and background noises. Often the secretive nature of calcifications reduces the credibility of efficient diagnosis, and in most times it is difficult to identify whether calcifications are benign or malignant. Therefore, extracting the breast region precisely from a mammogram is an essential step for automatic segmentation during computer-aided diagnosis and classification of disease state. In this study, we have evaluated the efficacy of three most widely used image denoising methods (median filter, Gaussian filter and Weiner filter) for fast and accurate detection of micro- or macro-calcification using Otsu-thresholding technique, using mammogram images of MIAS database. This systematic analysis revealed a simple and accurate image processing framework for the detection of heterogeneous calcification in Medio Lateral oblique (MLO) view of breast mammograms. For performance evaluation, three different classical filters were applied to various mammogram images with heterogeneous breast densities (fatty, dense, dense granular). The efficacy of the present method was verified based on several performance indices and found to be similar to that of other complex segmentation techniques. Overall, these results show a simple and efficient way of segmenting mammogram calcification using real data and can be applied to analyze other abnormalities in mammogram images for breast cancer diagnosis.

Keywords*—Breast Cancer; Mammograms; Calcification; Image Preprocessing; Image Segmentation; Computer-aided Diagnosis*

I. INTRODUCTION

Breast cancer has been the second major cause of cancer death amongst women, which is widely diagnosed with mammogram examination [1-3]. Among numerous imaging techniques used screen breast cancer, one of the most common reliable and non-invasive methods for breast cancer detection is mammography, which can visualize the internal anatomy of the breast tissue, including calcification and the presence of malignant cells. Early and accurate detection of breast cancer, based on digital mammogram images is important to develop computer-aided diagnosis system and reduce its risks. Breast calcifications are thought to be classified easily using mammography technique, in which each breast is typically imaged under two distinct views, i.e., the mediolateral oblique (MLO) view and cranial caudal (CC) view [1-3]. Although the MLO view gives the best view of the lateral side of the breast and seems to be the most common site for pathological changes, the morphology of calcification in mammogram images significantly vary depending on the breast density and other factors like older age, earlier wound, or an infection in the breast tissue. Therefore, identification of micro calcification and/or macro calcification have been highly challenging in image-based screening of breast cancer. Specifically, it is often difficult to differentiate the suspicious calcifications from normally benign variations in a given image as they appear on a mammogram in the form of tiny, bright white spots. Thus, a robust image preprocessing system must be defined before one develops more sophisticated and complex segmentation algorithms [12-18]. Image segmentation is a fundamental step in computer-aided analysis of mammograms, in which the foreground breast tissue is segmented out of the mammogram and used for disease prediction. However, the presence of background noises, masses, cluster of calcifications, architectural distortion and other artefacts (tags, pectoral muscles and non-breast regions) in mammograms challenges the efficacy of most image segmentation algorithms[11-15].

In this view, numerous algorithms have been proposed for pre-processing and segmentation of breast images. Yet, speed, accuracy and reliability of abnormality detection (e.g., micro- or macro-calcification) not only depends on the characteristics and types of calcification but also depends on the choice of pre-processing steps [1-3,14]. Thresholding (global and local) has

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been a most popular method used in digital image processing, which transforms the higher intensity pixel values to distinguish foreground objects from the background, based on an arbitrary threshold value [6-11]. For mammogram segmentation, Ibrahim et al.(2009), developed a method using a fixed threshold value of 18 and demonstrated its suitability for segmentation of breast images [17]. Similarly, Qayyum and Basit (2016) used Otsu's thresholding method to several breast images, showing its ability to segment nearly 96.89 % of the image dataset [18]. For image denoising, several techniques (such as median filtering, Weiner filtering, Gaussian filtering, adaptive medial filtering, Gaussian filtering and hybrid median filtering) have also been proposed, which is applied before the segmentation step [8-9].

Although threshold-based algorithms seem simple and easy to implement, application of global thresholding to MLO mammograms and its efficacy in calcification detection with heterogeneous breast density remained unexplored. Furthermore, it is unclear if classical noise removal techniques has any implications on preserving the size and shape of individual calcifications during threshold-based segmentation process. In recent years, several machine leaning and deep learning algorithms have been extensively applied to improve mammogram segmentation quality in classification and detection of breast lesions. However, despite their promising performances in tumor classification processes, accuracy of these training-based algorithms mostly relies on mammogram pre-processing and feature extraction steps. A computationally simple and efficient segmentation framework may help in identifying microcalcifications in mammogram images that are typically buried with a variety of background noises.

Therefore, in this work, we have explored the effectiveness of three widely used noise removal techniques (e.g., Wiener filter, Gaussian filter and median filter) on efficacy of global thresholding-based segmentation of calcification in mammogram images. Using both normal and malignant mammogram images from MIAS database, it was demonstrated that the classical threshold-based segmentation method provide a simple and powerful means of detecting calcifications during computer-aided diagnosis of breast cancer. The outline of the paper is as follows. Section II briefly describes the proposed segmentation workflow and noise removal methods used in this study. This also presents an overview of mammogram dataset used to develop and validate the present framework. Section III describes the results and performance analysis of image pre-processing methods and segmentation of mammograms with different breast density features. Section IV presents the conclusions drawn from this present study, and the scopes for future application of the current approach.

II. MATERIALS AND METHODS

A. *Mammogram Image Database*

In this section, we have discussed the source and characteristics of mammographic image data that are publicly available and used in this study. Mammographic Image Analysis Society (MIAS) is one of the most popular mammographic datasets compiled by a consortium of UK research organizations in 2015 [6]. The original MIAS database, digitized in the order of 50-µm pixel edge, was reduced to a 200-µm pixel edge and padded to obtain each image of size, 1024 ×1024 pixels. All images are stored in portable grey map (.pgm) format and are 8-bit grey level scale images with the dynamic intensity range as [0–255]. According to the features of the background tissues, it is basically classified into three different classes: fatty, fatty-glandular, and dense-glandular. These classifications are further split into benign, normal, and malignant conditions. It comprises of 206 normal and 116 abnormal cases (64 benign and 52 malignant). Although this database contains images in both mediolateral oblique (MLO) and cranial caudal (CC) view, only MLO view images were considered for present analysis.

B. *Image Pre-processiong and Segmentation Workflow*

The main difficulties in reliable detection of calcifications from mammogram images are the heterogeneity of background tissues, and the variations in the noise level which is often hardly exceeded by the signal itself. Noises in mammogram images are basically the random fluctuations or variations in the brightness, which may be produced while capturing the image. Different types of noises (e.g., Gaussian noise, salt & paper noise, speckle noise and poisson noise) may present in mammogram images, may affect the entire image processing and diagnosis stages. Therefore, three different types of denoising filters were selected in this study, and their performances are evaluated based on the peak-signal to noise ratio using MLO images of MIAS database. Specifically, median filter, Weiner filter and Gaussian filters were used to define the appropriate filtering for various background tissues such as fatty, fatty granular and dense granular. For image enhancement, histogram equalization was applied to the original MLO images. Figure 1 shows the proposed workflow for the segmentation of calcifications in MLO images.

Fig. 1. The workflow for efficient denoising using classical filters and microcalcification segmentation uisng breast mammograms.

Wiener filter used in this study is a linear filter that limits the noise amount present in the mammogram image by comparing

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it with the desired noiseless signal estimate. Wiener filters are characterized by an assumption of the stationary linear stochastic processes of image and noise with known spectral characteristics or known autocorrelation, cross-correlation, and the filter must be physically realizable [9-12].

However, it can destroy lines and other fine image details, blurs sharp edges and make poor performance in the presence of signal dependent noise, like in all other linear filters [6-9]. The Gaussian filter detects a peak on the basis that peaks are to be impulses. This filter basically corrects the spectral coefficient of interest, and all the amplitude spectrum coefficients within the filter window. This is linear low pass filter and the pixels near the edge have higher significance, thus reduces edge blurring.

In contrast, the median filter is a nonlinear spatial filter which replaces each pixel value with the median of surrounding neighborhood of the pixel with respect to the window size. It effectively removes impulse noise without shifting boundaries or reducing contrast. But it affects all pixels regardless of noise content. Adaptive median filters overcome this problem by changing the widow size adaptively while filtering process. For each pixel it calculates the median value as in the median filtering process and compares the median obtained with a threshold and decides either replaces the pixel, keep the pixel, or increase the neighborhood size and recalculate. Thus it only affects the image pixels with noise content [4].

C. Image Segmentation

For all the mammogram images, Otsu thresholding was applied after image pre-processing and morphological operation steps of Figure 1. Basically, in threshold-based segmentation, for a given threshold value *T*, the input image I_m, with the pixel intensity *i* get transformed into a binary intensity image, with two ranges of intensities $i > t$ and $i \leq t$, which conventionally denote the foreground and background of the image respectively. In our case, it is required to determine the optimal threshold value that can ideally separate the foreground calcification region from the background one.

Otsu's thresholding covers all possible thresholds and calculates the pixel values on each side of the threshold. This method selects a *k*-value that separates the foreground from the background based on the chosen threshold. It uses Intra-class variance, which is the weighted sum of the respective foreground and background variances [6].

In brief, its basic principle is to split the image pixels into two classes, and confirms the best threshold value through the variance maximum value between the two classes [refs]. Supposed that $G = [0, L - 1]$ is the range of grayscale of image $f(x,y)$ and p_i is the probability of every grayscale, and the threshold value t has splitted the image in two classes which are $C_0 = [0,t]$, and $C_1 = [t+1, L-1]$. The probability associated with each class is $\alpha_0 = \sum_{i=0}^{t} p_i$ and $\alpha_1 = 1 - \alpha_0$ respectively. The average gray value of the two classes are $\mu_0 = \sum_{i=0}^{t} \frac{ip_i}{\alpha_0} = \frac{\mu_t}{\alpha 0}$ and $\mu_1 = \sum_{i=t+1}^{L-1} \frac{ip_i}{\alpha_1} = \frac{\mu - \mu_t}{1 - \alpha 0}$ respectively. The criterion function has been defined as variance between the two classes, expressed as:

$$\beta^2(t) = \alpha_0(\mu_0 - \mu)^2 + \alpha_1(\mu_1 - \mu)^2 \qquad (1)$$

Based on the calculation using Eq. (1) above, we can obtain the maximum threshold *t* as desired.

D. Implimentation and Performance Evaluation

The implementation of three different filters, Otsu global thresholding algorithm and all statistical computation were performed in MATLAB R2021a. All simulations were done in a Pentium core i7, 8GB RAM, 1 TB HDD, 2.6 GHz desktop computer, in which it takes approximately 2-3 min for each algorithm to complete the segmentation task.

For performance analysis of WF, GF, AMF, we calculate two quality indices such as Peak Signal-to-Noise ratio (PSNR) and Mean Squared Error (MSE) for each MLO image. PSNR is a ratio between the maximum possible value and the value of corrupting noise of a signal that has an influence on the quality of its representation. It is proved that a filter having higher PSNR value is considered to be the best filter [ref]. Similarly, MSE indicates how close the filtered output is to the input image. Smaller the MSE value, closer will be the fitness of input and filtered output image.

III. RESULTS AND ANALYSIS

In this section a detailed analysis of the type of calcifications abnormality present in MIAS data, comparision of performances of three filter methods for image denoising and efficiency of Otsu thresholding method for calcification detection are provided.

A. Calcification in mammogram images with different baground

In first step, a set of MLO mammogram images with three distinct types of background tissues (fatty (F), fatty-glandular (G) and dense-glandular (D)) were chosen to evaluate the performance of the proposed framework in Figure 1. Figure 2 shows the representative images of a normal mammogram and three types of background noises with calcifications. By visual inspection it is apparent that the bright spots are difficult to separate from the malignant breast masses. These images were used for further pre-processing as described below.

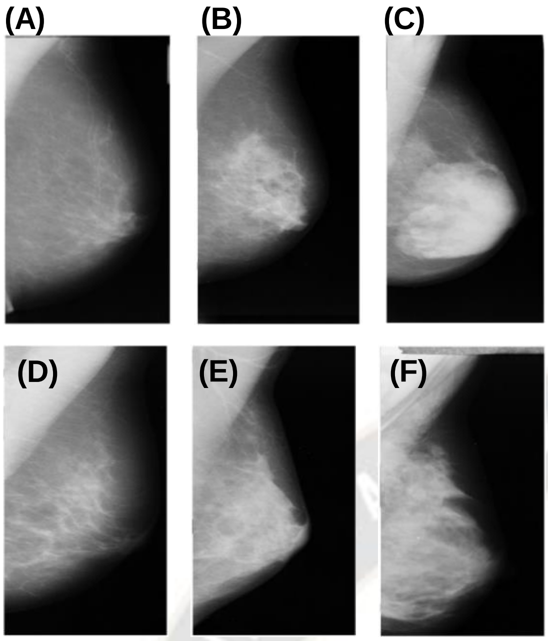

Fig. 2. Shown here is the presence of heterogeneous brest density in a set of normal mammogram images of left (A-C) and right (D-F) breasts in MLO views, with three different background noises (e.g., A:fatty; B: fatty-glandular and C: dense-glandular) without any known calcifications from MIAS database[6].

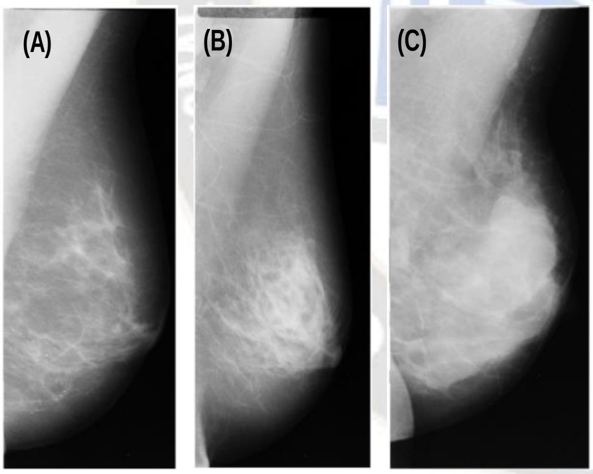

Fig. 3. Shown here is the presence of indistinguishable micro- and macro-calcifications the mammogram images of left breast in MLO views with the presence of various background noises: (A) fatty, (B) fatty-glandular and (C) dense-glandular from MIAS database[6].

B. Effect of denoising and image enhancements on mammogram images

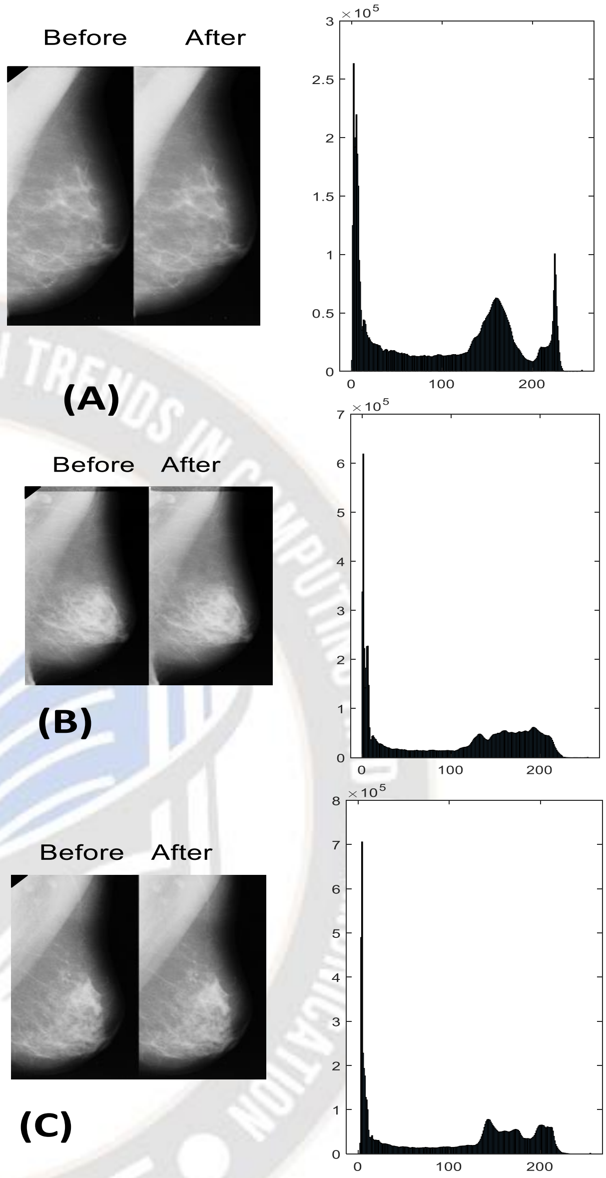

Fig. 4. Shown are the effects of denoising and contrast enhancement on calcification of MLO images of left breast after application of Wiener filters for (A) fatty, (B) fatty-glandular and (C) dense-glandular background tissues for the three MIAS data mdb245ls, mdb211lm and mdb249lm.

A comparison among three widely used filtering techniques is made in the presence of four different kinds of noises (Gaussian noise, Speckle noise, Poisson noise) and the computed peak-signal-to-noise ratio (PSNR) and mean square error (MSE) are summarized in Table 1 & 2. It was observed that the Adaptive filter method performance is better both visually and in terms of these indices.

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TABLE I. COMPARISON OF FILTER PERFORMANCES BASED ON PSNR VALUES FOR THREE BACKGROUND TISSUES IN MLO MAMMOGRAMS OF MIAS-DATABASE[6].

Method	Salt & Paper	Gaussian	Speckle	Poisson
Wiener Filter	15.9208	16.3230	17.3631	18.0930
Gaussian Filter	17.424	18.294	15.821	17.627
Median Filter	17.898	19.973	18.331	19.198

TABLE II. COMPARISON OF FILTER PERFORMANCES BASED ON MSE VALUES FOR THREE BACKGROUND TISSUES IN MLO MAMMOGRAMS OF MIAS-DATABASE.

Method	Salt & Paper	Gaussian	Speckle	Poisson
Wiener Filter	14.836	18. 624	19.485	10.527
Gaussian Filter	12.836	10. 624	11.485	9.527
Median Filter	9.836	8. 624	9.486	8.527

C. Calcification Segmentation using Otsu Thresholding

This section demonstrates the robustness of Otsu threshold algorithm in segmentation of microcalcifications in different types of MLO mammograms, used in this study. The same was applied to other images confirming the flexibility of thresholding method in segmenting of mammograms with varying noises.

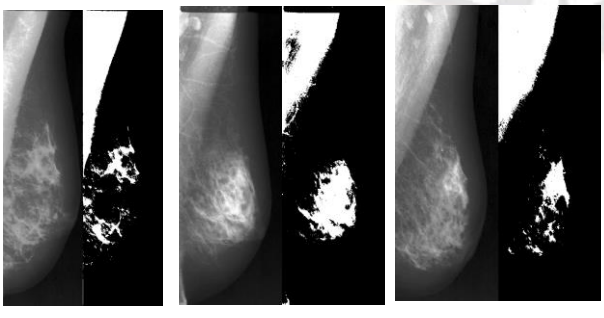

Fig. 5. Shown are the segmented mammogram images of three types backgrounds and indicating the regions of calcifications using three MIAS data mdb245ls, mdb211lm and mdb249lm.

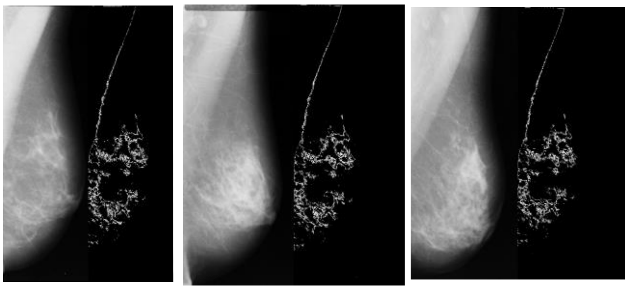

Fig. 6. Shown are the detected calcifications in the mammogram images of fatty, fatty-glandular and dense-glandular background noises.

In order to depict the intensity distribution of the fatty, fatty-glandular and dense-glandular breast tissues, the histogram of the respective three mammograms are shown in Figure 4. The average execution time of the present thresholding algorithm for segmentation of different mammograms are calculated for comparison. It was found that the computation time for segmenting fatty tissue images is around 0.0125 sec, for fatty-glandular 0.0132 sec and for dense-glandular 0.0129 sec, which is faster compared to other segmentation algorithms.

IV. CONCLUSION

This study was designed to develop a simple unified approach for segmenting calcifications in mammogram images, which is crucial automatic classification and prediction of breast cancer from a computational stand point. The publicly available mammogram data from MIAS database were analyzed systematically, to examine the impacts of various filter types in denoising the digital images. Histogram equalization was applied to enhance the contrast of the selected images and a threshold-based algorithm (Global Otsu thresholding) was applied to each breast image to detect the calcification regions. Their performance was tested on the different types of images such as Dense-Glandular, Fatty and Fatty-Glandular. The effectiveness of segmentation was assessed based on its computation time and resulting calcification regions. This study confirms that Otsu thresholding [5] can be applied to noisy mammograms to accurately detect microcalcifications and found to be computationally simple and easy to implement for large dataset.

One of the key observations in the present analysis is that the mammogram views and type of denoising method used have significant impact on the speed of segmentation process. However, the described framework is able fulfil the important constraints of preserving the size and shape of the individual calcification clusters. Even though the proposed framework has improved the segmentation performance of left and right MLO with varying density, some issues still need to be addressed.

First, this study uses a smaller amount of image data and no image enhancement strategies are used to expand the dataset. Hence, model performance are limited to this datasets. Second, the detection of microcalcification clusters is crucial in the diagnosis of breast cancer [1-6]. In this view, the present framework only focuses on the initial pre-processing stages and tried to identify the individual calcification candidates. Whereas, subsequent analysis are required for grouping candidates into clusters and removing any false-positive [2-5]. The approach presented in this study is sufficient to quantify image quality and object detectability for MLO imaging modality by removing anatomical background noises. Nevertheless, we feel that the simple Otsu threshold-based mammogram segmentation can provide a very useful diagnostic tool and can be applied to other mammogram abnormalities for early and accurate detection of lesions in breast cancer diagnosis.

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